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Comparative Analysis of Sigmoidal Feedforward Artificial Neural Networks and Radial Basis Function Networks Approach for Localization in Wireless Sensor Networks

Ashish Payal, C. S. Rai, B. V. R. Reddy

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***Abstract*—**With the increasing use and application of Wireless Sensor Networks (WSN), need has arisen to explore them in more effective and efficient manner. An important area which can bring efficiency to WSNs is the localization process, which refers to the estimation of the position of wireless sensor nodes in an ad hoc network setting, in reference to a coordinate system that may be internal or external to the network. In this paper, we have done comparison and analysed Sigmoidal Feedforward Artificial Neural Networks (SFFANNs) and Radial Basis Function (RBF) networks for developing localization framework in WSNs. The presented work utilizes the Received Signal Strength Indicator (RSSI), measured by static node on 100 x 100 m^2 grid from three anchor nodes. The comprehensive evaluation of these approaches is done using MATLAB software. The simulation results effectively demonstrate that FFANNs based sensor motes will show better localization accuracy as compared to RBF.

***Keywords*—**Localization, wireless sensor networks, artificial neural network, radial basis function, multi-layer perceptron, backpropagation, RSSI**.**

I. Introduction

LOCALIZATION process in a WSN is a critical process which may jeopardise the objective of the deployment of the WSN if it is not done in an optimum and efficient way. Various enabling technological advances in VLSI, MEMS, and wireless communications, have resulted in the development of small multifunctional wireless sensor nodes [1]. WSNs are a wide network of multiple sensor motes which provide data about their surroundings by communicating with each other. Disaster management [2], biomedical health monitoring [3] and military operations [4] are some WSN applications where localization plays a crucial role. Location-aware applications are being developed by researchers for road traffic control [5], asset tracking, autonomous robotic movement, and navigation [6]-[8]. Effective localization improves quality of coverage services and geographical routing. Efficient localization methods are being tried and tested to minimize the hardware cost, power cost, and deployment cost for large scale WSNs deployment. In WSNs, the localization algorithms use relative coordinate system, i.e. sensor nodes calculate coordinates with respect to each other but have no relationship with absolute coordinate system as depicted in Fig. 1. The very basic approach for determining a sensor mote's position is by collecting information about a mote's neighborhood i.e. proximity based techniques. In this way, the finite range of wireless communications helps in determining the position or location of motes with the help of beacon nodes (also called anchor nodes). Proximity-based technique suffers from the problem of several overlapping anchors. The geometric properties of two communicating sensor motes are also one of the prevalent techniques in localization. When distance between two sensor motes is used, it is called lateration and when angles between two motes are used it is called angulation. Both lateration and angulation methods suffer from the problem of imperfect measurement of distances and angles.

Ashish Payal, C. S. Rai, and B. V. R. Reddy are with the University School of Information & Communication Technology, GGS Indraprastha University, New Delhi, India (e-mail: ashish.ipu@gmail.com, csrai_ipu@yahoo.com, bvrreddy64@rediffmail.com).

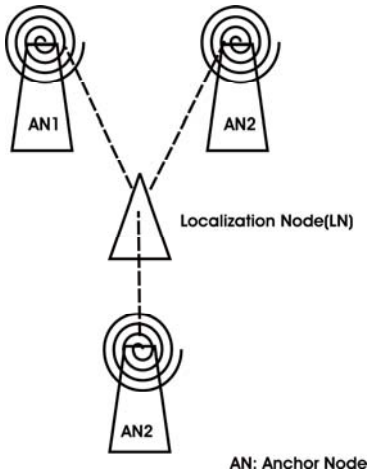


Fig. 1 Localization Scenario in WSNs [9]

II. Related Work

Several localization techniques have been proposed for WSNs starting from hyperbolic technique of Multilateration [10], Multidimensional scaling [11], convex optimization [12] and triangulation [13]. The localization methods can be categorized into two main classes, i.e. range-based and range-free localization classes [14]. In recent years, RSSI and Link Quality Indicator (LQI) value are used as intelligent technique for localization of sensor nodes taking in consideration the

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presence of noise sources in the real world WSN applications. Many ANNs based localization frameworks are proposed [15]-[17]. ANNs based localization techniques are capable of representing complicated relationship between input and output variables, and acquire knowledge about these relationships directly from the data [18]. Multi-layer perceptron (MLP) model is widely used type of FFANNs for localization in WSN. In [19], the MLP, ANN is evaluated with thirteen backpropagation training algorithms with RSSI as input and coordinates (location) as output. In context of sigmoidal feedforward ANNs, theoretical results for ANN assert that one single hidden layer network with sufficient numbers of sigmoidal nodes (in the hidden layer) are capable of approximating any continuous function arbitrarily well [20]-[22]. This property allows us to conjecture that if RSSI values are measured at least three anchor node positions (as done in triangulation) for a node at a specified point in 2-dimensional space; then SFFANNs may be designed which takes as input the RSSI values measured at the anchor nodes and predicts the coordinates of the node radiating the signal. This approach has been used in some of the reported works [23]-[25], [18], [16].

III. SFFANNs and RBF

MLP is a type of feedforward neural network that uses error back propagation algorithm in a supervised manner. In back propagation algorithm, error can be back propagated to adjust the weights to reduce the error between the actual output and the estimated output. In MLP, one or more hidden layers enable the complex tasks trained by extracting more meaningful features from the input vectors progressively with high degree of connectivity. It is a generalization of the Widrow-Hoff [26] learning rule to multiple-layer networks and nonlinear differentiable transfer functions and thus is known as error back propagation methods.

MLP uses backpropagation algorithm (gradient) to modify weights of each neuron to minimize mean square error (MSE) between the output and real values.

$$X_{k+1} = X_k - \eta_k g_k \tag{1}$$

where X_{k+1} is a vector of weights and biases, g_k is the gradient, η_k is the learning rate.

The MLP architecture used for the analysis is depicted in Fig. 2.

In our case, $RSSI_1$, $RSSI_2$, and $RSSI_3$ (Inputs) are multiplied by the input layer to hidden layer weights with w_{ij} representing the connection strength between the i^{th} hidden node and the j^{th} input and summed over the inputs to obtain the net input to the i^{th} hidden node' as:

$$n_i = \sum_{j=1}^{3} w_{ij} RSSI_j + \theta_i \tag{2}$$

where θ_i is called bias. The net input to the hidden node is transformed by a non-linear (activation function) which is required to be monotonically increasing, bounded, continuous, and differentiable. The usually used activation functions are the *logistic* function (also called the *logsigmoid* function):

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{3}$$

and the *hyperbolic-tangent* function (*tansigmoid* function):

$$\sigma(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{4}$$

Due to the odd-function symmetry of the hyperbolic-tangent function, it is used as an activation function. The output of the hidden nodes is multiplied by the connection strength parameters α_{ij} and summed over the hidden node index to obtain the i^{th} output of the network as:

$$x_i = \sum_{j=1}^{H} \alpha_{ij} \sigma(n_j) + \gamma_i \tag{5}$$

where $i = \{1,2\}$, H is the number of hidden nodes, $x_1=X$ and $x_2= Y$, and γ represents the threshold parameter / weight of the output node'.

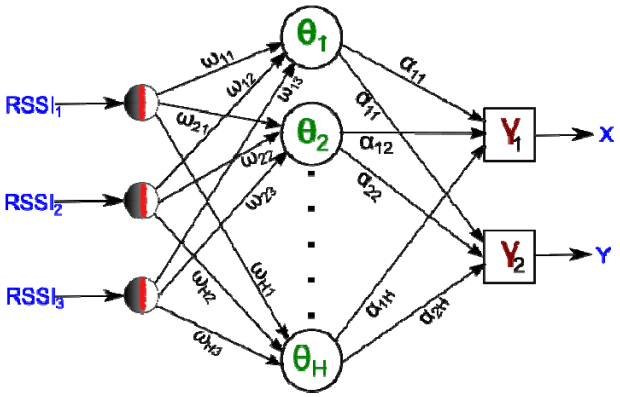


Fig. 2 Two layer MLP model

The weights of the network (w, α, θ, γ) as a group (and for the sake of brevity are collectively known as weights) are initialized to small random values and the inputs (RSSI values) are presented to the network to predict the coordinates of the transmitting mote. If we assume that the predicted values are (x,y) *vis-a-viz* the actual values (X,Y), the mismatch between the desired and the target value is represented as the average over all input-output pairs of the squared error:

$$E = \frac{1}{4}\left((X-x)^2 + (Y-y)^2\right) \tag{6}$$

To develop a SFFANNs model for any problem, the associated error functional E, is minimized by using a non-linear optimization technique, to obtain a set of weights for

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which the value of E is minimized over all data used for modeling.

Cover's theorem on the separability of patterns [27] lays the foundation for RBF as a classification method.

In [28]-[30] Position Model, Position-Velocity Model (PV) and Position-Velocity-Acceleration models (PVA) of the extended Kalman filters were compared with MLP and RBF for accuracy, robustness for solving localization problems.

A function F (interpolating surface) in RBF technique has the form:

$$F(x)=\sum_{i=1}^{N} w_i \phi\left(\|x-x_i\|\right) \tag{7}$$

where $\phi\left(\|x-x_i\|\right)$ for i=1,2,...,N is a set of N nonlinear RBFs.

These types of RBF networks are trained with input layer, hidden layer, and summation layer (output) to perform complex pattern-classification task. The RBF architecture as depicted in Fig. 3 is used for our analysis study.

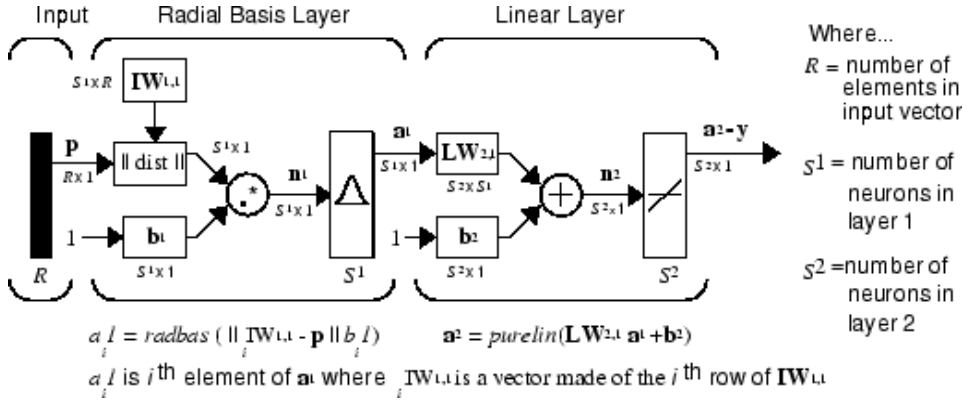


Fig. 3 Radial Basis Architecture [31]

IV. Simulation Design

In our simulation design, we have considered a WSN scenario containing 3 Anchor Nodes (ANs) and 118 grid sensors (red dots) deployed on the intersection of 100 x 100 m^2 as depicted in Fig. 4. For generating training data (RSS value), we used the simple path loss model [32] between 3 ANs (AN_1, AN_2, and AN_3) and 118 grid sensors.

According to this model, the received power at distance d is given by (8):

$$\overline{PL(d)}=\overline{PL(d_o)}+10n\log\left(\frac{d}{d_o}\right) \tag{8}$$

where *n* is the path loss exponent and varies with propagation environments.

The coordinates of three Anchor Nodes (ANs) are given in Table I.

TABLE I
AN Coordinates

Anchor Node	Coordinates(X,Y)
AN_1	(100,0)
AN_2	(100,100)
AN_3	(0,100)

MLP is trained on 118 samples and tested on 2000 non-error test samples as shown in Table II.

SFFANN consisting of one hidden layer is implemented using MATLAB 7.9.0 [31]. Two training matrices are formed from the simulation namely input and target matrices. The input matrix contains the RSSI column vectors from every anchor mote. Each RSSI vector contains RSS values obtained from three anchor nodes. RBF network is also implemented by using MATLAB 7.9.0.

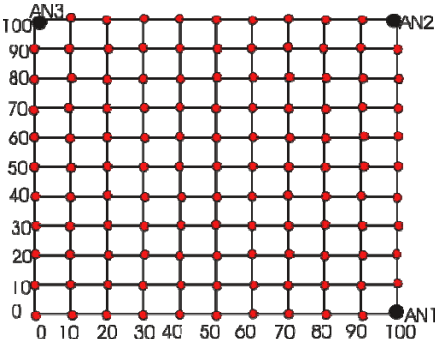


Fig. 4 Simulation Grid (100x100 m^2)

TABLE II
Sample RSS Data

Training sample	AN1	AN2	AN3	X_a	Y_a
1	-13.6	-14.9	-13.6	0	0
2	-13.1	-14.7	-13.6	10	0
…..	-12.7	-14.5	-13.6	20	0
118	-13.6	-4.4	-13.1	90	100

Hyperbolic-tangen(tansigmoid) transfer function is used for hidden layer and *linear* transfer function for output layer is used. SFFANNs were trained with no error and tested with 2000 non-error test samples.

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V. Simulation Results and Discussions

Localization error (LE) is the distance between the estimated coordinates (X_{est}, Y_{est}) and the actual coordinates of sensor node (X_a, Y_a).

$$LE = \sqrt{(X_{est} - X_a)^2 - (Y_{est} - Y_a)^2} \quad (9)$$

TABLE III
Comparative Statistical Results

Type of ANN	Mean Localization Error	Standard Deviation	R-square
MLP	5.15	1.6718	0.97
RBF	6.07	12.69	0.88

Table III contains the mean localization error, standard deviation, and R-squared values. These statistical parameters show the performance of the MLP and RBF. The mean localization error of 5.15 m is shown by MLP. When network is trained using MLP then finding the relative location of the sensor motes will be in the proximity of 5.15 m of real location, whereas in RBF network the mean localization error is of 6.07 m. Fitness of the available data is represented by R-square statistical parameter. Its value lies between 0 and 1. R-square value of 0.97 indicates that MLP explains all variability in the data.

Variation of different statistical results related to the performance of MLP and RBF is shown in Fig. 5.

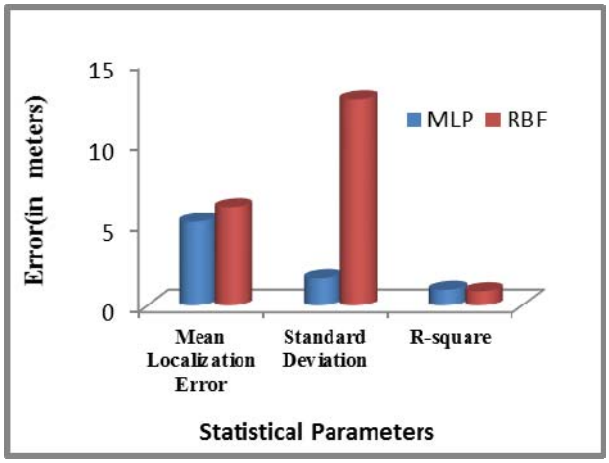


Fig. 5 Statistical Results

VI. Conclusions

The purpose of this comparative analysis between SFFANNs and RBF network approach is for developing efficient localization framework for WSNs. Both ANN models estimate the localization error by using RSSI values. Performance comparison in terms of mean localization error, standard deviation, and R-square statistical parameters has been done. The simulation results indicate that MLP has best performance in terms of accuracy. The MLP modeling can be a better choice for developing robust hardware for localization in WSNs. Further, these SFFANNs can be used for developing efficient localization framework. In comparison to RBF, MLP shows better localization accuracy, and computational performance. With many WSN applications relying on localization algorithms, this approach shall be extended for outdoor environment with special emphasis on three-dimensional localization applications in WSNs.

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